Vol. 5, Issue II, 2026 (April – June) DOI: https://doi.org/10.5281/zenodo.19660860

International Journal of Politics & Social Sciences Review (IJPSSR)

Website: https://ijpssr.org.pk/ OJS: https://ojs.ijpssr.org.pk/ Email: ijpssrjournal@gmail.com

ISSN 2959-6467 (Online) :: ISSN 2959-6459 (Print)
ISSN 2959-6459 (ISSN-L)
Recognized by Higher Education Commission (HEC), Government of Pakistan

Artificial Intelligence and Burnout among Professionals: The Moderating Role of Cognitive Efficacy

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Abstract

The increasing integration of the artificial intelligence (AI) into the professional environments has transformed the work processes while the raising concerns about the employee well being and the burnout. This study aimed to examine a relationship between the AI usage and a burnout with particular focus on moderating role of the cognitive efficacy among the clinical and organizational professionals. A quantitative cross-sectional research design was employed. A total of 180 professionals participated in the study, including 100 clinical and 80 organizational professionals selected through purposive sampling based on their exposure to AI tools in the workplace. Standardized measures, including the Maslach Burnout Inventory, a Cognitive Efficacy Scale, and an AI Usage Intensity Scale, were administered via an online survey. Data were analyzed using Pearson correlation, multiple regression, and moderation analysis. Results indicated that AI usage significantly predicted burnout, whereas cognitive efficacy was negatively associated with burnout. Furthermore, cognitive efficacy significantly moderated the relationship between AI usage and burnout, such that individuals with higher cognitive efficacy reported lower levels of burnout despite increased AI engagement. Additionally, clinical professionals demonstrated higher levels of emotional exhaustion compared to their organizational counterparts. The findings highlight dual impact of the AI as both a job demand or resource, emphasizing the protective role of cognitive efficacy. Implications for organizational training and psychological resilience interventions are discussed.

Keywords Artificial Intelligence; Burnout; Cognitive Efficacy; Technostress; Job Demands–Resources Model; Moderation Analysis; Occupational Well-being

Introduction

The rapid advancement and integration of the artificial intelligence in professional environments have fundamentally transformed how work is performed across both clinical and organizational domains. AI-driven systems are increasingly used for decision-making, data analysis, administrative automation, and workflow optimization, offering potential benefits such as increased efficiency and reduced manual workload (Raisch & Krakowski, 2021; Dwivedi et al., 2023). However, emerging evidence suggests that rather than simplifying work, AI may intensify job demands by accelerating task pace, increasing monitoring responsibilities, and requiring continuous cognitive engagement (Jarrahi et al., 2023; Tarafdar et al., 2025).

Burnout is a condition of long-term psychological exhaustion that arises due to the extended work-related pressures. It is commonly manifested in the form of emotional exhaustion an unemotional or impersonal attitude towards work and a loss of personal effectiveness (Maslach and Leiter, 2016). In clinical settings the integration of digital systems and AI tools has been linked with increased documentation burden and cognitive overload contributing to higher levels of emotional exhaustion (Shanafelt et al., 2022). Similarly organizational professionals report technostress decision fatigue and performance pressure associated with AI adoption (Ayyagari et al., 2011; Tarafdar et al., 2020). Recent studies highlight a growing phenomenon of "AI-induced cognitive fatigue," where continuous interaction with intelligent systems leads to mental strain and reduced cognitive clarity (Verma et al., 2025).

From the perspective of Job Demands Resources model and the AI can be conceptualized as both a job demand and a job resource. While it enhances efficiency and supports decision-making, it simultaneously imposes cognitive demands that may increase the risk of burnout if not adequately managed (Bakker & Demerouti, 2017; Wang et al., 2025). This dual nature makes it critical to identify psychological factors that can buffer the negative effects of AI-related demands.

One such factor is cognitive efficacy is defined as a personality's belief in their ability to effectively process manage and utilize cognitive resources in complex environments. Rooted in the Bandura's (1997) the self-efficacy theory cognitive efficacy has been associated with better problem-solving, adaptability, and resilience under stress (Salanova et al., 2019). Individuals with higher cognitive efficacy are more likely to perceive demanding tasks as manageable challenges rather than overwhelming threats, thereby reducing the likelihood of burnout (Xanthopoulou et al., 2020). In technology-driven environments, cognitive efficacy may play a crucial role in enabling professionals to effectively interact with AI systems while minimizing cognitive strain.

Despite the growing body of literature on AI and workplace well-being, several important gaps remain. First, most existing studies have examined technostress or digital fatigue broadly, with limited focus on AI-specific cognitive demands (Tarafdar et al., 2025). Second, there is a lack of comparative research examining both clinical and organizational professionals within a single framework, despite their differing work demands and AI usage patterns. Third, moderation of cognitive efficacy in the relationship between the AI usage and burnout has not been intensively studied especially through quantitative empirical studies. It is crucial to address these gaps to achieve a more sophisticated perspective on how professionals will alter to AI-integrated workplaces.

Thus, the purpose of the current study is to study the connection between AI use and burnout in the clinical and the organizational professionals, and to study the mediating effect of cognitive efficacy. Combining insights into the JD-R model and self-efficacy theory, this study aims to add to the beginning of the research on AI-related occupational health.

Objectives

1. To study the point in which the AI usage and the burnout of professionals are connected.
2. To measure the interdependence of the cognitive efficacy and burnout.
3. To explore the role of cognitive efficacy that moderates the relationship between AI use and burnout.
4. To make an analogy on the level of burnout in clinical and organizational professionals.

Hypotheses

H1: AI usage is the positively associated with burnout among professionals.
H2: Cognitive efficacy is negatively associated with burnout.
H3: Cognitive efficacy significantly predicts burnout among professionals.
H4: The relationship between the AI usage and burnout is mediated by cognitive efficacy i.e. the weaker the relationship is the higher the level of cognitive efficacy.
H5: Clinical professionals report higher levels of burnout compared to organizational professionals.

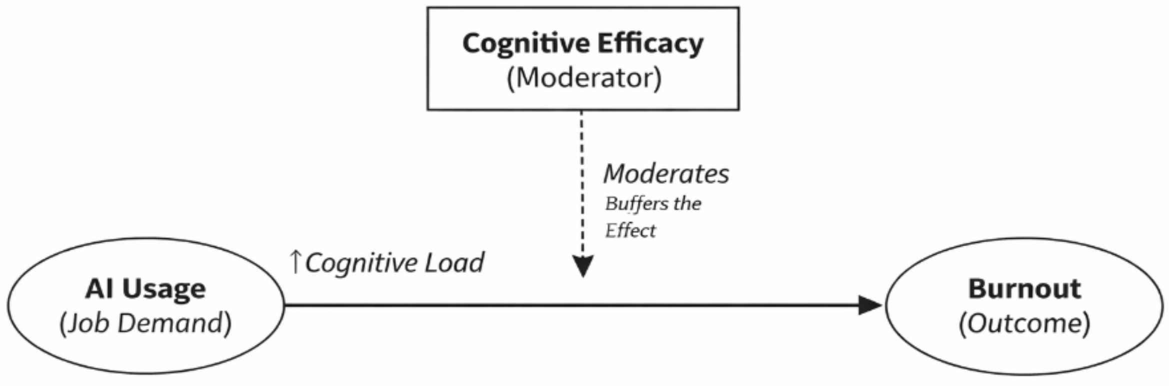

Figure 1. *The Theoretical Framework: AI Usage, Cognitive Efficacy, and Burnout.*

Figure 1. Theoretical Framework of AI Usage, Cognitive Efficacy, and Burnout

Methodology

Research Design

The current research used quantitative cross-sectional correlational research design to study the association between the artificial intelligence use and burnout, and determine the moderating effect of cognitive efficacy in professionals. This design was the appropriate as it allowed for analysis of relationships among variables at single point in the time without manipulation.

Participants

The total of 180 professionals participated in the study using purposive sampling. The sample comprised:

- Clinical professionals (n = 100) (e.g., psychologists, healthcare practitioners)
- Organizational professionals (n = 80) (e.g., corporate employees, managers)

The contestants ranged in age from the 25 to 55 years and had minimum of the one year of professional experience. Inclusion criteria required participants to have prior exposure to AI-based tools in their work settings. The unequal distribution reflects natural accessibility across professional domains.

Instruments

1. Burnout

The instrument that was measured using Maslach Burnout Inventory is burnout, and burnout measures: Emotional Exhaustion, Depersonalization, Personal Accomplishment.

The scale is consists of 22 items rated on the 7-point Likert scale (0 = Never to 6 = Always). The scores on the higher scale show greater levels of burnout. MBI has been shown to possess good the reliability as well as validity among the professional populations.

2. Cognitive Efficacy

Cognitive efficacy was assessed using an adapted Cognitive Efficacy Scale grounded in Bandura’s (1997) self-efficacy theory. The scale was designed to measure individuals’ perceived ability to effectively process information, manage complex tasks, and solve problems in cognitively demanding environments.

The scale was a list of 12 items rated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) such that an individual higher score on the scale reflects higher cognitive efficacy.

Items were contextually adapted to reflect AI-integrated work environments, ensuring relevance to modern professional settings. Content validity was established through expert review, and the scale demonstrated strong internal consistency in the present study (Cronbach’s α = .89).

3. AI Usage Intensity

The utilization of AI was evaluated with an AI Usage Intensive Scale developed by the researcher aimed at evaluating the frequency and scope of artificial intelligence application in work activities. The scale measured three main items: frequency of using AI task dependency on AI and the role of AI in decision-making processes.

The scale was composed of 10 items to be measured through a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) with those scores being higher suggesting increased AI engagement.

The scale itself was pilot tested on a small sample (n = 30) in order to make sure that it was understandable and relevant. The established validity was the content which was defined by the professional review of psychologists and organizational behavior professionals. The internal scale consistency was good (Cronbach 087 =.87) in the current study which means that it had good reliability.

Procedure

The survey was an online survey platform used in collecting the data. The participants were contacted through professional networks and online platforms. Prior to participation informed consent was obtained and ensuring confidentiality and voluntary participation. The questionnaire included demographic information followed by the three standardized scales. The average completion time was approximately 10–15 minutes.

Ethical Considerations

Ethical guidelines were strictly followed. Participants were informed about the purpose of the study and their right to withdraw at any time and the confidentiality of their responses. No identifying information was collected.

Data Analysis

The SPSS (Version 26) was used to analyze the data.). The statistical methods used were the following ones:

- Descriptive statistics (means, SDs)
- Pearson correlation analysis to test the relations between variables.

Various regression modeling to determine predictive relationships.

To examine the moderating effect of cognitive efficacy, moderate analysis will be used (PROCESS Macro, Model 1).

A significance level of $p < .05$ was used for all analyses.

Common Method Bias

Since self-report measures were used to gather the data at one time, the risk of common method bias was taken into account. To address this concern, procedural remedies such as ensuring anonymity and reducing evaluation apprehension were applied during data collection. Additionally, Harman's single-factor test was conducted, and the results indicated that no single factor accounted for the majority of the variance, suggesting that common method bias was not a significant concern in this study.

Control Variables

To enhance the robustness of the findings, key demographic variables including age, professional experience, and professional group (clinical vs. organizational) were considered as control variables during the analysis. Controlling for these variables helped ensure that the observed relationships among AI usage, cognitive efficacy, and burnout were not influenced by demographic differences.

Results

Reliability Analysis

Table 1

Reliability Analysis of Study Variables (N = 180)

Variable	No.of Items	Cronbach's Alpha (α)
AI Usage Intensity	10	.87
Cognitive Efficacy	12	.89
Burnout (MBI Total)	22	.91

All variables showed strong internal consistency (α > .80) indicating the scales were reliable for the further analysis.

Descriptive Statistics and Correlation Analysis

Table 2

Means, Standard Deviations, and Correlations (N = 180)

Variable	M	SD	1	2	3
1. AI Usage	3.62	0.74	—		
2. Cognitive Efficacy	3.85	0.68	-.21**	—	
3. Burnout	3.47	0.81	.45**	-.39**	—

Note. $p < .05$, $p < .01$

AI usage showed a significant positive correlation with the burnout ($r = .45, p < .01$) indicating that the higher AI engagement is associated with the increased burnout. Cognitive efficacy was negatively correlated with burnout ($r = -.39, p < .01$), suggesting its protective role. Additionally, AI usage was negatively related to cognitive efficacy.

Regression Analysis

Table 3

Multiple Regression Predicting Burnout

Predictor	B	SE B	β	t	p
Constant	1.12	.34	—	3.29	.001
AI Usage	.48	.07	.41	6.85	< .001
Cognitive Efficacy	-.42	.08	-.36	-5.21	< .001

$R^2 = .38$, $F(2,177) = 54.21$, p < p < .01

AI usage significantly predicted burnout (β = .41, p < p < .01), while cognitive efficacy significantly negatively predicted burnout (β = −.36, p < p < .01). Together the predictors explained 38% of the variance in burnout.

Moderation Analysis

Table 4

Moderation Analysis (AI Usage × Cognitive Efficacy → Burnout)

Predictor	B	SE B	t	p
AI Usage	.44	.08	5.50	< .001
Cognitive Efficacy	-.39	.09	-4.33	< .001
AI Usage × Cognitive Efficacy	-.21	.06	-3.50	.001

The interaction term (AI Usage × Cognitive Efficacy) was the significant ($p < .01$) indicating that cognitive efficacy moderates the relationship between the artificial intelligence usage and burnout. Specifically the positive relationship between AI usage and the burnout weakens at higher levels of cognitive efficacy.

Table 5

Independent Samples t-test

Variable	Group	M	SD	t	p
Burnout	Clinical (n=100)	3.62	0.79	2.45	.015*
	Organizational (n=80)	3.29	0.81		

Clinical professionals reported significantly higher burnout compared to organizational professionals ($p < .05$).

Results Summary

The results indicated that AI usage was positively associated with burnout while cognitive efficacy was negatively associated with burnout. Regression analysis revealed that both AI usage and cognitive efficacy significantly predicted burnout explaining 38% of the variance. Moderation analysis further demonstrated that cognitive efficacy significantly buffered the relationship between AI usage and burnout. Additionally clinical professionals reported higher levels of burnout compared to organizational professionals.

Discussion

This study examined the relationship between artificial intelligence usage and burnout, while also exploring the moderating role of cognitive efficacy among clinical and organizational professionals. The findings offer empirical support for the proposed model and contribute to the existing literature on technology-driven work environments and occupational well-being. Consistent with H1 the results revealed that AI usage significantly and positively predicted burnout. This finding aligns with prior research suggesting that advanced technologies, while designed to improve efficiency, often intensify job demands by increasing cognitive load, multitasking requirements, and performance expectations (Jarrahi et al., 2023; Tarafdar et al., 2025). The concept of "technostress" and AI-induced cognitive fatigue has been increasingly recognized in recent studies where continuous interaction with intelligent systems leads to mental exhaustion and reduced the psychological well-being (Verma et al., 2025). In line with the Job Demands–Resources Model, AI in this context appears to function predominantly as a job demand, contributing to emotional exhaustion and burnout when cognitive resources are strained.

Supporting H2 and H3 the cognitive efficacy was found to be the negatively associated with the burnout and a significant predictor of reduced burnout levels. This result is consistent with the

Self-Efficacy Theory which posits that individuals with stronger beliefs in their cognitive abilities are better equipped to manage complex and demanding situations. Previous research has shown that higher self-efficacy enhances coping mechanisms reduces perceived stress and promotes adaptive functioning in high-demand environments (Salanova et al., 2019; Xanthopoulou et al., 2020). In the context of AI-driven work settings professionals with high cognitive efficacy may perceive AI not as a burden but as a manageable tool thereby reducing the likelihood of burnout.

Importantly the findings supported H4 the demonstrating that cognitive efficacy significantly moderates the relationship between the AI usage and burnout. Specifically the positive association between AI usage and burnout was weaker among individuals with higher cognitive efficacy. This indicates that cognitive efficacy functions as a **psychological buffer** altering the strength of the relationship rather than its direction. Individuals with the high cognitive efficacy are more capable of managing cognitive demands, interpreting AI-related challenges as manageable, and maintaining psychological resilience. In contrast, individuals with lower cognitive efficacy are the more vulnerable to the adverse effects of AI-induced demands leading to higher levels of burnout. This finding reinforces the Job Demands–Resources model by highlighting the critical role of personal resources in mitigating the negative impact of technological demands.

Regarding H5 the study found that clinical professionals reported significantly higher levels of burnout compared to organizational professionals. This result is consistent with the existing literature indicating that clinical roles involve additional emotional labor responsibility and administrative burden all of which are further intensified by digital and AI systems (Shanafelt et al., 2022). The integration of the AI in clinical settings often requires continuous attention, accuracy, and accountability, thereby increasing cognitive and emotional strain.

Overall the findings highlight the dual nature of AI as both a facilitator and a stressor. While AI offers opportunities for efficiency and innovation it simultaneously introduces cognitive challenges that may undermine well-being if not properly managed. The study extends the JD-R model by incorporating AI-specific demands and emphasizes critical role of cognitive efficacy as a buffering mechanism.

Limitations and Future Directions

This study has certain limitations that need to be considered. First the cross-sectional nature of the research restricts the ability to determine causal relationships among the variables. Future studies may benefit from using longitudinal or experimental approaches to better examine causal links. Second, the data were collected through self-reported measures which can lead to common method bias, although attempts were made to control it. Third, the use of purposive sampling may reduce the generalizability of the results to a wider population.

In addition the study did not include other relevant factors such as personality characteristics organizational support or technological competence which could also influence burnout. Future research should consider including these variables to develop a more comprehensive understanding.

Finally although both clinical and organizational professionals were included in the sample the unequal distribution between groups may affect comparison outcomes. Future studies are recommended to use more balanced or larger samples to improve the reliability and generalizability of findings.

Practical Implication

The findings of the suggest that the organizations should not only focus on implementing AI technologies but also invest in enhancing employees' cognitive efficacy through training, skill development and psychological support. Interventions aimed at improving cognitive adaptability and confidence may help mitigate burnout in AI-driven work environments.

Theoretical Contribution

This study contributes the growing literature by integrating AI usage into the JD-R framework and empirically demonstrating the moderating role of cognitive efficacy. It provides a more nuanced understanding of how personal resources interact with the technological demands in shaping occupational well-being.

Conclusion

This study highlights the complex role of artificial intelligence (AI) in shaping professional well-being demonstrating that increased AI usage is associated with higher levels of burnout among both clinical and organizational professionals. At the same time cognitive efficacy emerged as a crucial protective factor significantly reducing burnout and buffering the negative impact of AI-related demands. These findings underscore the dual nature of AI as both a resource and a stressor within modern work environments. Importantly the results emphasize that technological advancement alone is insufficient without parallel investment in human cognitive capacities. Strengthening cognitive efficacy through targeted training and support mechanisms can enhance adaptability and resilience enabling professionals to navigate AI-driven workplaces more effectively. Overall, this study contributes to a deeper understanding of the psychological implications of AI integration and highlights the need for balanced, human-centered approaches to technological implementation.

References

Ayyagari, R., Grover, V., & Purvis, R. (2011). Technostress: Technological antecedents and implications. *MIS Quarterly, 35*(4), 831–858.

Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology, 22*(3), 273–285. https://doi.org/10.1037/ocp0000056

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2023). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research. *International Journal of Information Management, 57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2020.101994

Jarrahi, M. H., Memariani, A., & Guha, S. (2023). The principles of human–AI interaction in workplace decision-making. *Business Horizons, 66*(4), 459–471. https://doi.org/10.1016/j.bushor.2023.01.002

Maslach, C., & Leiter, M. P. (2016). Understanding burnout: New models. In G. Fink (Ed.), *Stress: Concepts, cognition, emotion, and behavior* (pp. 351–357). Academic Press.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Salanova, M., Llorens, S., & Schaufeli, W. B. (2019). Yes, I can, I feel good, and I just do it! On gain cycles and spirals of efficacy beliefs, affect, and engagement. *Applied Psychology, 60*(2), 255–285.

Shanafelt, T. D., Dyrbye, L. N., & West, C. P. (2022). Addressing physician burnout: The way forward. *JAMA, 317*(9), 901–902. https://doi.org/10.1001/jama.2017.0076

Tarafdar, M., Pullins, E. B., & Ragu-Nathan, T. S. (2020). Technostress: Negative effect on performance and possible mitigations. *Information Systems Journal, 30*(1), 103–132. https://doi.org/10.1111/isj.12236

Tarafdar, M., Cooper, C. L., & Stich, J. F. (2025). The technostress trifecta: Tech invasion, overload, and complexity in AI-driven workplaces. *Journal of Organizational Behavior, 46*(2), 145–162.

Verma, N., Singh, A., & Gupta, R. (2025). Cognitive cost of artificial intelligence: Examining mental fatigue in digital work environments. *Computers in Human Behavior Reports, 10*, 100321.

Wang, B., Liu, Y., Qian, J., & Parker, S. K. (2025). Achieving effective remote working: A work design perspective. *Applied Psychology, 70*(1), 16–59.

Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2020). The role of personal resources in the job demands–resources model. *International Journal of Stress Management, 14*(2), 121–141.